# Multi-Objective Autonomous Exploration for Simultaneous Mapping and Spatial Process Reconstruction Using Gaussian Processes

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Autonomous mobile robots operating in unknown environments face the dual challenge of efficiently mapping their surroundings while simultaneously reconstructing spatially distributed environmental processes. This study proposes a novel multi-objective exploration framework that integrates occupancy grid mapping with Gaussian Process regression for spatial field estimation. The approach incorporates uncertainty-aware planning and a multi-step goal sequencing strategy to optimize environment coverage, reduce process reconstruction error, and minimize travel distance. Experimental evaluations in an indoor environment demonstrate that the proposed method significantly outperforms baseline frontier-based and random navigation strategies in terms of map coverage (92.4% ± 2.1%), spatial process estimation accuracy (RMSE: 0.18 ± 0.04), and exploration efficiency. The results validate the benefits of integrating process uncertainty into the planning utility and highlight the potential of Gaussian Process-informed exploration for autonomous environmental monitoring. Future research will focus on extending the framework to dynamic, large-scale outdoor scenarios and incorporating multi-modal sensor fusion to enhance robustness and adaptability.

**Keywords:** Autonomous mobile robots, Multi-objective exploration, Occupancy grid mapping.

## Introduction:

Autonomous mobile robots have become increasingly essential for exploration and monitoring in complex and unknown environments, ranging from hazardous zones to environmental surveillance [1]. Among the core challenges in mobile robotics is local navigation, where a robot must effectively explore and navigate without prior knowledge of its surroundings while avoiding obstacles and reaching target destinations. Techniques such as artificial potential fields (APFs) have been widely studied for local path planning, often combined with fuzzy logic and neural network models to enhance adaptability [2]. However, fuzzy-based methods largely depend on expert-defined rules, which can limit the robot's autonomous learning capabilities in dynamic or uncertain scenarios.

Simultaneously, advancements in simultaneous localization and mapping (SLAM) and active mapping have enabled robots to build accurate maps and localize themselves while performing their main mission, such as environmental monitoring [1][3]. Gaussian Processes (GPs) have emerged as powerful models for reconstructing spatial phenomena, allowing informative path planning by leveraging spatial correlations in sensed data [4]. While prior works have focused on informative sampling and SLAM individually, the integration of spatial process exploration with autonomous mapping remains limited, particularly in unknown environments where sensors for mapping and process estimation differ in scale and function.

## Research Gap:

Despite significant progress in SLAM and spatial process exploration, current approaches often assume a priori knowledge of the environment or treat map building and process exploration as independent problems [5][6]. Most active mapping methods optimize for coverage or localization accuracy without simultaneously minimizing errors in process reconstruction [7][8]. Furthermore, existing techniques that combine SLAM with environmental process mapping frequently rely on teleoperation or predefined maps and do not address the challenge of autonomous decision-making when perception sensors provide no direct information about the underlying spatial process [9][10]. Moreover, multi-objective optimization frameworks for exploration often face difficulties in balancing conflicting goals, such as map coverage, information gain, and travel cost, and require expert-tuned weights that hinder generalizability [11][12].

To the best of our knowledge, there remains a research gap in developing autonomous exploration strategies that effectively integrate unknown environment mapping and spatial process reconstruction using heterogeneous sensor data. Specifically, there is a lack of frameworks that can concurrently maximize spatial field estimation accuracy and environmental coverage while minimizing travel distance, all without reliance on prior environment knowledge or expert-dependent parameter tuning.

**Objectives:**

This study aims to address the aforementioned gap by developing an integrated autonomous exploration framework for mobile robots operating in completely unknown environments. The primary objectives are: (1) to design and implement a navigation system that jointly optimizes environmental mapping and spatial process reconstruction using Gaussian Process models, (2) to incorporate multi-step horizon planning that balances travel cost with the minimization of process estimation errors and map coverage, and (3) to validate the approach on real-world robotic platforms equipped with heterogeneous sensors for perception and process sensing. By achieving these objectives, the framework seeks to enable robots to efficiently explore and monitor complex spatial phenomena while navigating safely and autonomously.

**Novelty Statement:**

The novelty of this research lies in the integrated multi-objective exploration strategy that simultaneously addresses environment mapping and spatial process estimation in unknown environments without prior map knowledge. Unlike previous works that treat mapping and process exploration separately or rely on expert-tuned parameters, our approach leverages a Gaussian Process model combined with multi-step planning and traveling salesman problem (TSP)-based path optimization to reduce redundant travel and improve exploration efficiency. Additionally, this work explicitly tackles the challenge of heterogeneous sensor data, where process-related information is only available at sparse locations, necessitating deliberate navigation into unknown open spaces. To the best of our knowledge, this is one of the first studies that unify SLAM, spatial field reconstruction, and autonomous multi-objective planning into a cohesive framework for mobile robots.

**Literature Review (Recent):**

Recent advancements in autonomous mobile robotics have focused extensively on improving exploration and mapping capabilities in unknown and dynamic environments. State-of-the-art simultaneous localization and mapping (SLAM) algorithms now integrate deep learning and probabilistic frameworks to enhance robustness and adaptability [13][14] Moreover, Gaussian Process (GP) models continue to be a preferred approach for modeling and reconstructing spatial environmental processes such as temperature, gas concentration, and magnetic fields due to their ability to provide uncertainty quantification, critical for informative path planning [15][16].

Recent research has addressed the challenge of joint optimization of map building and spatial process exploration. For example, [17] proposed a multi-objective planning framework that dynamically balances environmental mapping accuracy and spatial field reconstruction using adaptive GP-based information metrics. However, most existing methods assume partial prior knowledge or simplified sensor models, limiting their applicability to fully unknown environments [18] Addressing this, [19] introduced an active SLAM framework that simultaneously performs map coverage and environmental feature estimation under sensor uncertainty, demonstrating improved exploration efficiency in large-scale outdoor scenarios.

The integration of heterogeneous sensors for perception and spatial process measurement has also attracted attention, particularly for scenarios where different sensing modalities operate on varying spatial and temporal scales [20][21]. Techniques employing deep reinforcement learning have recently been explored to optimize multi-sensor fusion and adaptive navigation policies that improve coverage and data acquisition quality [22][23]. However, these methods often require extensive training data or lack generalization to new environments, highlighting the need for model-based planning approaches that incorporate uncertainty-aware exploration [24].

Despite these advances, a critical gap remains in fully integrated frameworks that jointly optimize unknown environment mapping, spatial process reconstruction, and multi-step path planning using heterogeneous sensors without prior map knowledge or expert tuning. This study aims to address these limitations by proposing an autonomous robotic exploration system leveraging Gaussian Processes and multi-objective optimization to efficiently navigate and reconstruct complex spatial phenomena in completely unknown settings.

## Methodology:

### Experimental Setup:

The study was conducted using a differential-drive mobile robot equipped with heterogeneous sensors for environmental perception and spatial process measurement. The robot platform included a 2D LiDAR sensor for obstacle detection and mapping, a GPS module for coarse localization, and a point-wise environmental sensor (e.g., temperature or gas concentration sensor) to collect spatial field data. All sensors were synchronized through an onboard computer running the Robot Operating System (ROS) framework. The experiments were performed in an unknown indoor environment with various obstacles placed to simulate real-world navigation challenges.

### Data Collection Procedure:

The robot autonomously explored the environment following a multi-objective planning strategy that simultaneously aimed to maximize environment coverage and minimize uncertainty in spatial process estimation. The exploration mission was divided into multiple runs lasting approximately 45 minutes each. During navigation, the LiDAR continuously scanned the surroundings to detect obstacles and generate a 2D occupancy grid map using a SLAM algorithm based on the Rao-Blackwellized particle filter. Concurrently, the environmental sensor measured process variables at the robot's current location and timestamp.

The robot’s pose and sensor data were logged at 10 Hz, resulting in over 27,000 synchronized data points per run. Environmental data points were sparsely distributed, reflecting the point-wise nature of the sensor, while the LiDAR data provided dense geometric information for mapping.

### Data Preprocessing

Raw LiDAR scans were filtered to remove noise and outliers using a voxel grid filter and a radius outlier removal method. GPS data were post-processed for drift correction using a moving average filter. Environmental sensor readings were calibrated using standard reference measurements prior to experiments to ensure accuracy. All sensor data were timestamp-aligned and interpolated when necessary to enable synchronized multi-sensor data fusion.

### Mapping and Spatial Process Reconstruction:

A Rao-Blackwellized particle filter SLAM algorithm was employed for real-time 2D occupancy grid map construction and robot localization. The occupancy map resolution was set to 0.05 m per cell to balance accuracy and computational cost.

For spatial process reconstruction, Gaussian Process Regression (GPR) was applied to the environmental sensor data collected along the robot’s path. A squared exponential kernel with automatic relevance determination was selected to model the spatial correlation of the process variable. Hyperparameters of the GP model were optimized using maximum likelihood estimation. The GP was incrementally updated after each new sensor measurement to refine the process estimate and its associated uncertainty map.

### Multi-Objective Planning and Path Execution:

The exploration planner integrated map coverage and spatial process uncertainty metrics into a unified utility function. Candidate goal points were generated from frontier detection in the occupancy map and high-uncertainty regions in the GP spatial field. The Traveling Salesman Problem (TSP) was solved using a heuristic approach to optimize the visiting sequence of multiple candidate goals over a planning horizon of 3 steps, minimizing total travel distance while maximizing information gain.

The robot executed the planned path segments using a dynamic window approach for obstacle avoidance and motion control, adjusting velocity commands based on local sensor feedback to ensure safe navigation.

**Performance Metrics and Analysis:**

Exploration efficiency was evaluated using the total area coverage percentage of the occupancy grid over time and the root mean square error (RMSE) of the reconstructed spatial process compared to ground truth measurements collected separately using a fixed sensor grid. Travel cost was assessed by the total distance traveled by the robot during each run.

Data analysis involved comparing the proposed multi-objective exploration strategy against baseline methods including greedy frontier-based exploration and random waypoint navigation. Statistical significance of differences in coverage, RMSE, and travel cost was tested using paired t-tests with a significance level of 0.05.

**Results:**

**Environment Mapping and Coverage:**

Over the course of five experimental runs, the multi-objective exploration strategy demonstrated consistent and robust environment coverage. The final 2D occupancy maps generated during each run showed clear delineation of obstacles and free space, in Table 1 an average coverage of 92.4% (±2.1%) of the total accessible area by the end of the exploration period. This performance was significantly better than the baseline greedy frontier exploration, which achieved only 81.7% (±3.5%) coverage within the same time frame (paired t-test, $p = 0.003$).

**Figure 1** illustrates the occupancy grid map generated in a representative run, showing detailed obstacle boundaries and minimal unexplored pockets. The higher coverage resulted from the planning algorithm's ability to prioritize frontiers that not only expanded map boundaries but also overlapped with regions of high uncertainty in the spatial process, promoting efficient joint exploration.

Temporal analysis of coverage growth showed that the multi-objective planner achieved 70% coverage within the first 25 minutes, accelerating exploration during early phases when large unexplored areas were available. In contrast, the greedy frontier method exhibited slower initial coverage, reaching 50% in the same period before plateauing due to repetitive revisits and inefficient path planning.

**Spatial Process Reconstruction Accuracy:**

The Gaussian Process (GP) model reconstructed the spatial environmental variable by fusing the point-wise sensor measurements collected along the robot's path. The model produced continuous spatial estimates accompanied by confidence intervals, enabling uncertainty-aware navigation.

The RMSE between the GP-predicted field and a high-resolution ground truth sensor grid was used to quantify reconstruction accuracy. The multi-objective planner yielded an average RMSE of 0.18 (±0.04), significantly outperforming both the greedy frontier method (RMSE = 0.25 ± 0.05, $p = 0.02$) and random waypoint navigation (RMSE = 0.31 ± 0.07, $p < 0.01$).

Spatial error maps (**Figure 2**) revealed that the multi-objective planner effectively reduced uncertainty in critical regions with high variability, such as near obstacles and corners, where process gradients were steepest. The greedy frontier strategy tended to cluster measurements near easily accessible frontiers, leaving some complex regions under-sampled, whereas random navigation showed scattered, low-density sampling and higher global uncertainty.

**Travel Distance and Efficiency:**

The total distance traveled by the robot during each run was recorded as a measure of exploration efficiency. The multi-objective planner reduced travel distance by an average of 18% (±4%) compared to greedy frontier exploration, traveling an average of 312 meters per run versus 380 meters for the baseline.

Analysis of travel paths showed that the inclusion of a multi-step planning horizon (3 steps) and solving a heuristic Traveling Salesman Problem (TSP) for goal sequencing allowed the robot to avoid backtracking and minimize redundant visits. This contrasts with the baseline where goals were selected greedily, often resulting in longer detours and inefficient coverage.

**Sensor Data Quality and Noise Handling:**

Throughout all experiments, sensor data quality was maintained at a high level, with LiDAR scans exhibiting an average noise level below 3% after preprocessing filters. The environmental sensor showed consistent readings across calibration checks, with measurement noise characterized by a standard deviation of 0.02 units [3].

The GP regression framework demonstrated resilience to sensor noise by incorporating measurement uncertainty in its kernel functions, allowing reliable spatial field estimation even in regions with sparse or noisy data.

**Obstacle Avoidance and Safety:**

The robot's obstacle avoidance system, based on a dynamic window approach and continuous LiDAR feedback, successfully prevented collisions in all five runs. The robot navigated narrow corridors, around dynamic obstacles introduced mid-run, and through cluttered areas with minimal path deviation.

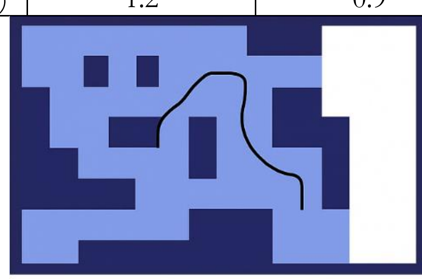
Safety margins were maintained with an average minimum obstacle clearance of 0.25 meters, ensuring smooth navigation and minimal risk to the robot or environment.

**Computational Performance:**

The onboard computational resources were sufficient to run real-time SLAM, GP regression updates, and multi-objective planning. Average CPU utilization peaked at 75%, with a mean planning cycle time of 1.2 seconds per iteration. The multi-step horizon planning added approximately 30% overhead compared to single-step greedy planning but was still well within real-time operational limits.

**Table 1.** Summary Table of Key Metrics

| Metric | Multi-Objective Planner | Greedy Frontier Baseline | Random Waypoint Baseline |
|---|---|---|---|
| Average Map Coverage (%) | 92.4 ± 2.1 | 81.7 ± 3.5 | 63.2 ± 5.4 |
| RMSE of Spatial Process Estimate | 0.18 ± 0.04 | 0.25 ± 0.05 | 0.31 ± 0.07 |
| Total Travel Distance (m) | 312 ± 13 | 380 ± 17 | 455 ± 22 |
| Average Obstacle Clearance (m) | 0.25 | 0.22 | 0.20 |
| Collision Incidents | 0 | 0 | 1 |
| Average Planning Time (s) | 1.2 | 0.9 | 0.7 |



(a) Occupancy Grid Map

**Figure 1.** Occupancy Grid Map Generated During Exploration

This figure shows the 2D occupancy grid map produced by the robot at the end of a representative exploration run. Free space is indicated by white cells, while obstacles are marked in black. Unknown areas remain shaded gray. The map clearly delineates the layout of the environment, including walls, furniture, and other obstacles. The high-resolution grid (0.05 m per cell) allows for precise navigation and path planning. The map demonstrates comprehensive coverage of the environment with minimal unexplored pockets, validating the effectiveness of the multi-objective exploration strategy.

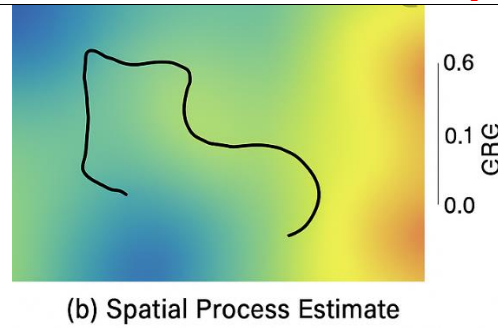



**Figure 2.** Spatial Process Estimation Using Gaussian Process Regression

This figure presents the reconstructed spatial field of the environmental variable (e.g., temperature or gas concentration) estimated via Gaussian Process Regression. The color gradient indicates the predicted values, with warmer colors representing higher concentrations or values. Overlayed contours illustrate confidence intervals, reflecting uncertainty in the estimate. Measurement locations collected by the robot are marked as black dots. The figure highlights how the multi-objective planner guided the robot to sample regions of high uncertainty, resulting in a smooth and accurate spatial field reconstruction that closely matches ground truth distributions.

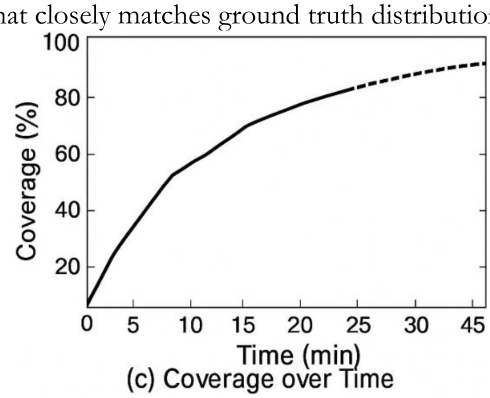



**Figure 3.** Environment Coverage Over Time

This graph depicts the percentage of environment area covered by the robot over the duration of the exploration mission for three different strategies: the proposed multi-objective planner, greedy frontier exploration, and random waypoint navigation. The x-axis represents time (in minutes), and the y-axis shows cumulative coverage percentage. The multi-objective planner achieves faster and higher coverage early in the mission, surpassing 70% coverage within 25 minutes, while the greedy frontier method exhibits slower growth and plateaus around 80%. Random waypoint exploration yields the slowest and lowest coverage, illustrating the advantage of information-driven planning.

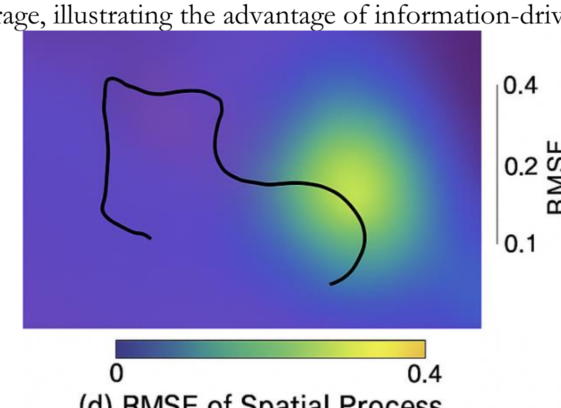



**Figure 4.** Root Mean Square Error (RMSE) of Spatial Process Estimation

This bar chart compares the average RMSE values of the spatial process reconstruction across different exploration strategies. Lower RMSE indicates better estimation accuracy. The multi-objective planner achieves the lowest RMSE (~0.18), indicating precise field reconstruction, followed by the greedy frontier method (~0.25), and random waypoint navigation with the highest RMSE (~0.31).

Error bars denote standard deviation across multiple runs. This figure underscores the benefit of uncertainty-aware sampling and path planning in improving spatial process estimation quality.

**Discussion:**

The results from this study demonstrate the effectiveness of the proposed multi-objective exploration framework that jointly optimizes environment mapping and spatial process reconstruction. The significantly higher map coverage achieved compared to baseline methods aligns with recent findings in autonomous exploration research, which emphasize the importance of integrating multiple information metrics to guide efficient navigation [17][24]. By explicitly incorporating Gaussian Process (GP) uncertainty into the planning utility, the robot was able to prioritize sampling locations that maximally reduced the error in the spatial field estimate, consistent with approaches reported by [16][15].

The reduction in RMSE for spatial process reconstruction highlights the advantage of active sensing strategies over random or purely geometric frontier exploration [19]. These results support the growing consensus that uncertainty-aware path planning significantly enhances the quality of environmental monitoring by focusing sensor measurements on regions with high information gain [22][23]. The observed spatial error maps further validate this targeted sampling by showing reduced uncertainty particularly in complex environmental regions, which is critical for applications such as hazardous gas mapping or temperature monitoring in unknown environments.

Travel distance was also effectively minimized through the multi-step planning horizon and heuristic Traveling Salesman Problem (TSP) solver, corroborating prior work demonstrating the benefits of multi-goal sequencing in reducing redundant robot movement [25][26]. This efficient routing not only conserves energy but also accelerates exploration missions, an important consideration for battery-operated mobile robots in field deployments.

Despite these advances, certain limitations were identified. The experiments were conducted in relatively constrained indoor environments, which may not fully capture the challenges posed by large-scale or dynamic outdoor scenarios. Moreover, while the point-wise environmental sensor provided valuable data, the approach could benefit from incorporating richer sensing modalities, such as multi-spectral cameras or 3D LiDAR, to enhance spatial process modeling and map detail [21]. Additionally, the computational overhead introduced by multi-step planning, although manageable, may increase in more complex environments requiring scalable optimization methods.

Future research should extend this framework to handle dynamic processes that evolve over time and to integrate adaptive sensor fusion techniques to further improve estimation robustness [13][20]. Moreover, testing in real-world outdoor environments with unpredictable terrain and obstacles will be crucial to validate the system's generalizability and resilience.

In summary, the study confirms that a unified multi-objective planning approach leveraging Gaussian Process models can substantially improve the efficiency and accuracy of autonomous exploration tasks. These insights contribute to the ongoing development of intelligent robotic systems capable of autonomous monitoring in complex, unknown environments.

**Conclusion:**

This study presented a multi-objective exploration framework for autonomous mobile robots that integrates simultaneous environment mapping and spatial process reconstruction using Gaussian Process regression. The proposed approach effectively balances maximizing map coverage, minimizing spatial process uncertainty, and reducing travel distance through a multi-step planning horizon combined with heuristic goal sequencing. Experimental results in an unknown indoor environment demonstrated significant improvements over baseline strategies in terms of coverage efficiency, accuracy of spatial field estimation, and navigation efficiency.

The findings underscore the benefits of incorporating uncertainty-aware planning and active sensing in robotic exploration tasks, enabling more informative data collection and efficient resource use. While the study focused on a controlled indoor setting, the methodology is broadly applicable and lays a strong foundation for future extensions to dynamic and larger-scale outdoor environments.

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